Developing Production-Ready, Artificially Intelligent mHealth Tools: Sentiment Analysis to Track Positivity

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Background. Disruptive behavior disorders, such as Attention Deficit/Hyperactivity Disorder, are common and costly.[1,2] Stimulant medication, behavioral treatment, and the combination of these two modalities are the leading evidence-based interventions for ADHD.[3] However, many children with disruptive behavior fail to receive treatment.[1,4] Previous efforts to leverage machine learning to address the unmet need for healthcare in this population include a game designed to assist with objective diagnosis,[5] sentiment analysis of social media to detect disordered behavior online,[6,7] and a smartwatch app that reinforces time management skills via generic computerized messages.[8] Recently, there has been a particular focus on computerized ADHD diagnosis, as accumulating efforts attempt to leverage supervised learning by training a variety of sources of data (e.g., surveys, computerized cognitive tasks, fMRI, EEG) on ground truth diagnoses determined by clinicians.[9–13] Computerized diagnosis of ADHD will be difficult to accomplish for several reasons: (1) clearly, applications will ethically require a low false positive rate to remain in accordance with the oath, "do no harm," (2) assigning an ADHD diagnosis is a relatively low base rate clinician behavior, occurring at most once per assessment session (a child can only be diagnosed with ADHD one time), (3) a hallmark of ADHD is intra-individual behavioral variability,[14] requiring observation of an individual in multiple domains across ample time, and (4) many of the symptoms of ADHD (e.g., inattention) are also symptoms of other mental health disorders, such as depression, further confounding differential diagnosis.[15] Given the nature of diagnosis and treatment for ADHD, perhaps machine learning techniques would be better suited to intervention than diagnosis. For example, a common element of evidence-based behavioral treatment for ADHD is "labelled praise."[16–18] That is, to reduce disruptive behavior among children with ADHD, an effective strategy for parents or teachers is to repeatedly say specific compliments (positive sentences) about a child's adaptive behavior. We advocate for the development of machine learning techniques focused on treatment for ADHD, such as increasing caregivers' rate of labelled praise (e.g., Huber et al.[19]). An artificially intelligent, treatment-focused mHealth application for ADHD (vs. diagnosis-focused) could leverage the benefits of machine learning, yet evade the challenges of computerized diagnosis.

Methods. The two main components of our "demo" were executed with machine learning algorithms. First, speech-to-text translation was implemented using the IBM Watson speech-to-text library. Second, we trained sentiment analysis models: we used a Convolutional Neural Network (CNN) for text classification created in Tensorflow with training data from an open source Google Library. The user interface of the application included visual/graphical displays, developed in the Angular framework and Javascript language. Data is encrypted using AES-128 bit standard. Lastly, data will be managed with Amazon DynamoDB, a NoSQL database service that supports key-value and document data structures.

Findings. An encrypted, browser-based application was developed: please see www.gracyas.net for a Minimum Viable Product (MVP), as well as Figures 1-4 in Appendix A. Preliminary work (n=1) revealed that speech-to-text translation and sentiment analysis appear to function within an acceptable range of time (e.g., within several minutes). Anecdotal evidence includes that the speech-to-text translated sentence, "Wow, Lucas! I am so proud of you for sitting in your chair!" received a sentiment value of 0.922 on a scale from 0 to 1 (0 = negative; 1 = positive). On the other hand, an unremarkable, neutral sentence, "I don't know how long this will take" received a value of 0.523. We defined positive sentences as a value > 0.5. See Table 1 for more sentiment analysis examples.

Future Directions. More research is needed to evaluate the accuracy of our algorithms and the effectiveness of our app on changing user behavior and functional outcomes as intended. However, our MVP demonstrates initial promise for a future app that could be used as a stepped care or adjunct intervention to track and increase the rate at which caregivers state positive sentences toward their child with ADHD. That is, a positivity tracker could be useful as a self-help application, or via individualized recommendations/collaborative monitoring at the direction of a mental health professional. Given the high rate at which compliments need to be repeatedly uttered, a positivity tracker would be helpful to caregivers in the way that a pedometer might be useful to obese individuals aiming to increase physical activity. Perhaps our application could also help accrue a corpus of language data to manually label to provide more specific (supervised or semi-supervised) feedback to caregivers in future iterations. If given the opportunity, we would solicit advice about: (1) what is the next logical step with respect to research/development? (2) with respect to attempts to obtain funding, what your recommendations? (3) to partner with industry, what should we consider next (e.g., patent)?

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